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Mapping and Modeling Urban Dynamics: A Critical Review of AI Algorithms and Their Application in Complex Urban Contexts.

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Abstract: *For efficient urban planning in a context where cities worldwide are subject to climate hazards, it remains necessary to implement computerized systems capable of performing the tasks of predicting and modeling urban expansion. This methodological review analyzed the performance of AI-based modeling techniques, such as machine learning algorithms (Random Forest (RF), Support Vector Machine (SVM), XGBoost) and deep learning algorithms (Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN)), recurrent neural networks (RNN), and their variants, from 2014 to 2025. The results demonstrate that machine learning models are better suited for land-use mapping, with high accuracy in classification processes. Deep learning techniques offer high performance in segmentation processes for extracting physical features from satellite or orthophoto images. However, regardless of the model and processing method used, the final accuracy is significantly dependent on the quality and resolution of the input data and the capabilities of the available computing resources. The analyzed scientific studies demonstrate that AI is a major asset for effective urban planning. However, experimenting with these algorithms in non-homogeneous urban contexts, such as those found in developing countries, and integrating non-physical data (socio-economic factors, etc.) would enable a holistic approach to managing urban phenomena.*

Keywords: *Artificial Intelligence, Deep Learning, Machine Learning, Mapping, Urban Prediction*

I. INTRODUCTION

Cities around the world have faced various natural hazards of all kinds due to climate change for several decades. Urban planning and risk prediction, particularly regarding the potential impact of urban changes on these hazards, have become major global challenges. The scientific community has spent decades developing and experimenting with urban prediction models. These models are primarily based on empirical methods, the most commonly used being cellular automata such as the SLEUTH and CA-Markov models. These models have demonstrated good performance in simulating homogeneous urban fabrics and have been widely applied in the United States, China, and elsewhere in the world [57, 9, 6, 25].

Despite this resounding success, researchers quickly realized the need to strengthen these models or find other prediction methods, given their limitations in integrating socio-economic factors and their sensitivities in non-homogeneous urban fabrics, which affected their accuracy. The development of artificial intelligence has enabled the experimentation of new urban simulation approaches based on Machine Learning (ML) and Deep Learning (DL). Several ML and DL techniques have been designed and tested in urban management by researchers: Random Forest (RF), Support Vector Machines (SVMs), and k- Means. Clustering algorithm, Gradient Boosting Machines (eg., Xgboost), and Time Series Analysis Convolutional Neural Networks (CNNs), Recurrent Neural Network (RNN) and Long Short- Term Memory (LSTM) network, Graph Neural Networks (GNNs), Variational Autoencoders (VAEs) and Transformer Neural Network (TNNs), Artificial Neural Networks (ANN) [37, 31, 16, 17]. These models have introduced a new understanding in urban space management, given their varied use which concerns: the prevention of road traffic flows and the intelligent optimization of traffic light control [14, 65, 29], the analysis and prediction of vulnerability to natural hazards [31], climate risk modeling [4, 29], urban prediction for efficient urban planning [16, 39, 17] but also the prediction and monitoring of greenhouse gas emissions in the world [5, 64]. These various possible applications of these models demonstrate their crosscutting nature in the management of urban planning as a whole. The performance of these models also lies in their ability to integrate multi-source data (from satellite imagery to socioeconomic data), enabling the creation of a robust processing architecture [4, 5, 63].

This review focuses on the application of these Machine Learning techniques (Random Forest, SVM and XGBoost) and Deep Learning (ANN, CNN, RNN and their variants) in the modeling of complex urban patterns, the associated performance of each model in the urban simulation process, from data acquisition to final processing, as well as their limitations.

II. METHODOLOGY OF THE REVIEW

A methodology based on the PRISMA approach [40] was adopted to establish a scientifically robust review framework. The databases of Scopus, ScienceDirect, Wiley Online Library, ResearchGate, and Google Scholar were consulted to gather relevant work in the urban context using machine learning (ML) and deep learning (DL) algorithms (Random Forest, SVM, XGboost, ANN, CNN, RNN, and their variants). Keywords: "Machine *Learning and Urban", "Deep Learning and Urban", "Urban" "Modeling," "AI,* «and " *GeoAI* " are the keywords used in the literature search process. The collected scientific articles and books underwent a rigorous process of analysis, filtering, and selection to create the final documentation. After eliminating duplicates in the filtering phase, the following criteria were defined:

- **Time criterion:** the 2014-2025 interval is defined for all projects.
- **Indexing criteria:** selection of works published in indexed journals,
- **Relevance criterion:** selection of works focusing on the integration of AI in urban management, including land use mapping and segmentation.

This process enabled the validation of 68 scientific works (Table 1), following a progressive exclusion based on various aspects: title, abstract, and full content. The synthetic analysis allowed for the definition of the principles of each model and the evaluation of their performance in the urban context in order to assess their limitations.

Table 1: Summary of the selection procedure

Element	Description
Covered period	2014 – 2025
Databases consulted	Scopus, ScienceDirect , Wiley, ResearchGate , Google Scholar
Keywords used	Machine Learning and Urban, Deep Learning and Urban, GeoAI , Urban Modeling AI
Documents identified (before filtering)	89
Duplicates removed	0
Documents remaining for filtering by title	89
Articles excluded after reading the title	15
Articles remaining for summary reading	74
Articles excluded after reading the summary	6
Articles reviewed in full text	68
Final number of articles included in the journal	68
Topics covered	LULC classification, urban segmentation, urban prediction, spatiotemporal simulation
Methods studied	RF, SVM, XGBoost , ANN, CNN, RNN, LSTM, U-Net, Mask R-

Element	Description
	CNN
Data types	Optical satellite imagery, SAR, UAVs, socio-economic data

III. MACHINE LEARNING

3.1 Principle

Machine learning is a branch of artificial intelligence that involves equipping and training computer systems to perform tasks that would normally require human intervention [26]. Machine learning models represent automatic learning models. These models enable learning without a specific program. They involve implementing various mathematical models based on statistics, optimization, and computer science, allowing for analysis, interpretation, prediction, and so on. Implementing such algorithms requires powerful tools such as R and Python [47].

Implementing these models requires human-machine interaction. The nature of this interaction will depend on the work environment, the nature and complexity of the data, and the expected outcome of the experiment. Machine learning can be divided into three categories:

- Supervised learning: the model is trained on labeled data to generate results,
- Unsupervised learning: the model examines unlabeled data to discover hidden structures,
- Reinforcement learning: the model acquires its skills by interacting with an environment, receiving rewards or penalties according to its actions, like an agent learning to play a video game [47].

Several Machine Learning models have been designed over time and applied in various sectors, including the most robust:

- Vector Machine Support
- Random Forest,
- Xgboost,

Among the best-known machine learning models, the **Support Vector Machine (SVM)** relies on a process of finding an optimal hyperplane. This hyperplane serves to separate the different classes at the input. The model has demonstrated its effectiveness in simplifying fairly complex phenomena by maximizing the amplitude separating the different classes grouped by the hyperplane, thus making the model robust. The processing of complex datasets and the modeling of nonlinear phenomena are possible thanks to the model's use of kernel functions. This justifies its relevance in remote sensing classification [42].

Random Forest model, for its part, falls into the category of ensemble models by combining various machine learning algorithms. The model is primarily characterized by the implementation of completely independent decision trees. For each tree, the model incorporates a different sample combined with a random subset. The goal is to reduce variance while preserving complexity by using the average predictions of several trees. This avoids the risk of overfitting. In conclusion, this model is the result of a weighted average across all the trees. Its efficiency in processing large datasets and its ability to estimate the relative importance of different elements within the ensemble make it a robust model [52, 35].

XGBoost (**Extreme Gradient Boosting)** is another powerful model, also based on decision trees. Through iteration, the algorithm identifies and corrects residual errors from previous iterations, enabling optimal predictions. Known for eliminating the risk of overfitting, the model is also robust**,** characterized by its fast execution speed during processing phases and its ability to handle very large datasets. These aspects have allowed its application by researchers in various fields [44,42].

3.2 RF, SVM and XGboost algorithms in urban space management

Urban space management is one of the areas where machine learning continues to be explored by the research community worldwide. Managing this space involves several disciplines, such as remote sensing, GIS, and others. The key element for efficient urban management remains obtaining reliable, georeferenced data within a defined timeframe. This data, often in the form of satellite imagery or orthophotos, is acquired using remote sensing and photogrammetry techniques. Once acquired, it is processed to extract information about the urban environment, such as land cover. To optimize execution time and ensure the accuracy of land cover maps, machine learning algorithms demonstrate significant potential. Several studies have investigated the contribution of approaches based on SVM, Random Forest, and XGBoost models. [48] applied SVM to model land cover change in the municipality of Zemun, Serbia, from 2001 to 2011, considering nine land use classes. The study highlights the need for well-chosen explanatory variables, balanced sampling, and optimized hyperparameters. This work also underscores the sensitivity of the SVM model to class imbalance and the quality of input data. The work of [45]**,** integrating Random Forest for object-oriented classification with spectral data, textural measurements, and spatial metrics, and applied to the city of Ciudad Juárez, Mexico, successfully overcame the limitations of classical land cover mapping techniques. The research results demonstrated an overall accuracy of 92.3% and a kappa coefficient of 0.896. The implemented method successfully discriminated between non-homogeneous urban classes. The study's main contribution is the model's ability to generate a land-use map without relying on socioeconomic information in a data-constrained environment. However, the quality of such an approach is highly correlated with the quality and resolution of the images used. Furthermore, there is the need for manual selection of spatial metrics and the difficulty of separating mixed land-use categories. **[8]** adopted a similar approach using Random Forest to extract 21 urban land-use and land-cover classes, including, but not limited to, homogeneous surfaces (water, extensive vegetation) and non-homogeneous structures (residential, industrial, and infrastructure areas). This was achieved through multi-resolution segmentation integrated with object-oriented classification (OBIA). Based on a hierarchical schema, such as three data levels, the study applied in the Chinese metropolitan area implements such a large-scale urban classification technique. This strategy also required the integration of medium- and very-high-resolution satellite imagery (GF-1 and GF-2), respectively. The study achieved an overall level 2 accuracy of 89% and a level 3 accuracy of 87%, further demonstrating its usefulness for land-use mapping. However, the approach, which relies on high-resolution imagery, must be able to capture the local context, and there is also the possibility of confounding urban classes. This is the main limitation of the study. [23] presented an ensemble-based AI model using XGBoost. The study, which was applied in the area of Beijing enclosed by the Fifth Ring Road, aims for a fine-grained classification with nine urban land-use classes. In the overall model, the authors combined two specific variable spaces: physical space and socioeconomic space. Image segmentation helped create these two spaces. The authors combined social detection data (data based on points of interest and social media records) with physical data (satellite imagery). The model can assess the importance of these aspects. The average accuracy of the results is 74.2%. The methods demonstrated the model's effectiveness in assessing land-use types. However, the accuracy of this approach is highly dependent on the quality of the satellite imagery, and depending on the social media data used, it could be subject to bias and thus influence predictive accuracy.

All these studies have shown the sensitivity of the models to the quality and resolution of the integrated satellite images. The question of which of these approaches performs best has been raised several times by researchers. **[1]** conducted a comparative study of three land cover models and Deep Learning. The study, carried out in a complex boreal landscape of south-central Sweden (mixed land cover zone) near the Uppsala region, considered eight land cover classes. Using multi-temporal Sentinel-2 imagery (spring, summer, autumn, winter) and **1477 samples** for each class (split 70% for training, 30% for validation), the results were as follows: overall accuracy of 0.758 ± 0.017 for SVM, 0.751 ± 0.017 for XGBoost, 0.739 ± 0.018 for Random Forest, and 0.733 ± 0.0023 for Deep Learning. These results demonstrate the superiority of the SVM model in land cover mapping within this specific context. The overall accuracy achieved, while reasonable, is not excellent, hence the need for further experimentation and improvement of the model. Deep Learning performs less well than other models. This may suggest that the model's architecture might not be fully suited to Deep Learning. This comparative study is not the only one being conducted by the research community (Table 2).

Table 2: Summary of comparative work between SVM, RANDOM FOREST and XGBoost

Reference	Study area	Data	Algorithms / Models	Methodology	Results / Performance	Contributions	Boundaries
[1]	Northern landscape, Sweden	Sentinel -2 multi-temporal (spring, summer, autumn, winter)	SVM, Random Forest, XGBoost, Deep Learning	LCLU classification into 8 classes, stratified sampling, statistical tests	SVM ≈ 75.8%, XGBoost ≈ 75.1%, RF ≈ 73.9%, DL ≈ 73.3%	Rigorous comparison of ML algorithms in a boreal context	Moderate performance
[55]	Fire-affected areas, China	Sentinel -2 post --fire	Random Forest (RF), SVM	LULC classification + post-fire change detection -, cross-validation	RF 88%, SVM 85%	Evaluates the robustness of the models for post-fire changes -.	Specific to fire-affected areas
[18]	Urban development, China	Multiple sources: Landsat 8, socio- -economic indices	RF, SVM, XGBoost, ANN	Predicting the intensity of urban development, selecting variables by importance	XGBoost ≈ 91%, RF ≈ 89%, SVM ≈ 87%, ANN ≈ 85%	Evaluates the ML for the quantitative prediction of urban development	Dependence on the quality and availability of socio-economic data
[61]	Urban area, China	GF -6 satellite, multi- features (spectral, textural, geometric)	RF, SVM, XGBoost	Object-oriented LULC classification, multi- -feature optimization	RF ≈ 92%, SVM ≈ 89%, XGBoost ≈ 91%	feature optimization - combined with OBIA, high precision in an urban context	Depends on the quality of the GF -6 images
[49]	Urban areas, China	Integrated data: optics + SAR	RF, XGBoost	Mapping of urban impermeable surfaces, fusion of multi-sensor data	RF ≈ 90%, XGBoost ≈ 92%	Integrated optics + SAR for improved urban waterproof classification	Dependence on multi-sensor data

All of these studies have demonstrated the capabilities of machine learning algorithms in processing geospatial data at the urban scale, particularly in supervised land cover classification. While effective, these algorithms have all shown sensitivity to the quality and resolution of the satellite imagery used as input data. This is not their only limitation; when faced with more or less complex datasets and more robust processing tasks such as the detection of urban and rural areas, they require reinforcement through enhanced training and parameter optimization. Deep learning techniques can be suitable in these situations. However, these limitations do not diminish the ability of these algorithms to provide high accuracy in land

IV. DEEP LEARNING

4.1 Principle

Deep Learning is a branch of machine learning. It is a robust and efficient machine learning technique that uses deep artificial neural networks. The model integrates several layers of interconnected neurons into the learning process. This feature allows the model to learn autonomously. In fact, the model itself identifies and extracts the training variables, a characteristic that distinguishes it from traditional machine learning techniques. This learning approach makes the model suitable for processing large and complex datasets [2, 66]. Several Deep Learning models have been conceptualized and adopted, the main ones being:

- **Convolutional Neural Networks (CNNs)**

They are used in spatial analysis and image analysis and have the ability to automatically detect different patterns (textures, shapes, objects etc.). In remote sensing, their contribution to the processes of satellite image classification, change detection or land cover mapping is considerable [28, 19, 60].

- **Recurrent Neural Networks (RNNs)**

These algorithms are designed for processing sequential data (text, time series, etc.). In the context of urban management, they are perfectly suited for spatiotemporal studies, particularly for monitoring urban sprawl, climate change, and natural hazards [50, 12, 54, 24]. Variants of RNNs include LSTM (Long Short- Term Memory) and GRU (Gated Restricted Unit). Recurrent Units). They strengthen RNNs in managing long-term dependencies.

- **Autoencoders**

They are used in compression processes, size reduction, and anomaly detection [27,67]. In the preparation and pre-analysis stage of satellite or topographic data, these autoencoders are very useful in the process [33].

- GANs (Generative Adversarial Networks)

The model consists of simultaneously training networks (a generator network and a discriminator network). The model is adaptable to the simulation of high-resolution images, but especially to the reconstruction of areas assumed to be masked in satellite images [32, 64].

In addition to these models, there are artificial neural networks (ANNs). These different deep learning architectures have demonstrated their adaptability to large and complex datasets with unsupervised or weakly supervised learning capabilities [30]. However, they require significant computing resources (GPU/TPU). The risk of overfitting when data is quantitatively limited must be considered [51]

4.2 Applications of ANN, CNN, RNN algorithms and their variants in urban space management

Among the algorithms tested by researchers due to their high performance in managing and analyzing urban composition, neural networks have proven particularly suitable. In the chapter «GeoAI *for Urban Detection,*" [7] presents several applications of AI algorithms in the urban context. Based on concrete cases from the city of Singapore, the study highlighted the use of deep learning algorithms to quantify elements that were previously difficult to measure (green roofs and solar installations, urban noise, human comfort, quality of public spaces) using satellite imagery, street photography, and other data. The accuracy of the results obtained marks a turning point in the applicability of these models to urban planning. Nevertheless, significant limitations are noted, such as the sensitivity of the models to data quality, the difficulty of reproducing workflows due to partial access to data and/or code, and the limited geographical generalization of the studies.

In a 2020 study conducted in the city of Irbid, Jordan, [17] combined the classic hybrid urban simulation model CA-Markov with an artificial neural network (ANN) model, incorporating explanatory variables such as slope, distance to roads, and altitudes. This model led to an improvement in the accuracy of the urban simulation, reaching 90% compared to 86% for CA-Markov alone. The approach proposed by the authors facilitates the spatial mapping of areas with high urbanization potential. However, the model's sensitivity to data quality and the assumption of continuity of past trends constitute significant limitations. Other relevant studies using artificial neural networks have been conducted over the last 10 years (Table 3).

Table 3: Relevant studies applying ANNs in urban space management

Authors	Data used	Method / Algorithm	Main results	Advantages / Limitations
[16]	geospatial data, development plans	Artificial Neural Network (ANN) integrated with neighborhood analysis	Improved predictions of urban growth by taking into account future development areas	Model specific to Ar-Ramtha , requires detailed local data
[58]	Open spatial data (social, economic, biophysical, etc.)	Artificial Neural Network (ANN)	Urban growth predictions for 2030, with exit maps for each city	Applicability to other European areas thanks to pan-European datasets
[62]	High temporal resolution land use data	ANN integrated with cellular automata and the Markov chain	Accurate simulation of urban expansion in a rapidly urbanizing area	Requires high temporal resolution land use data
[41]	Signal loss measurement data	Artificial Neural Network (ANN)	A more precise and flexible model compared to conventional linear models	Not directly related to urban growth, but applicable to urban infrastructure
[38]	Local geospatial data	Artificial Neural Network (ANN)	Identifying non-linear relationships in urban growth	Theoretical model, requires empirical validation

Artificial neural networks have demonstrated superior performance in urban simulation, whether or not combined with empirical prediction techniques such as CA-Markov. The robustness of the algorithm allows for the implementation of large urban datasets. However, several other deep learning algorithms, such as convolutional neural networks, have shown tremendous capabilities in various aspects of urban environments, particularly in the semantic segmentation of urban areas, urban traffic scenes [11], and remote sensing images [34].

Within this segmentation dynamic, [22]**,** seeking to improve the accuracy of building extraction in complex urban environments, tested an optimized version of Mask R-CNN incorporating ResNetXt101 variants and a spatial attention module. The study, based on aerial images acquired by drones (UAVs), demonstrates 95% accuracy in building extraction. This accuracy surpasses that of basic CNN algorithms and those of R-CNN, Fast R-CNN, Faster R-CNN, and GAN. The contribution of this research lies in the reduction of false positives and the improvement in edge delimitation. However, the sensitivity to variations in image brightness constitutes a major limitation of the implemented approach. Furthermore, the model's high computational resource requirements are a significant constraint. Further testing of the model in other heterogeneous and homogeneous urban contexts is warranted to better quantify biases and sensitivity and to ensure parameter optimization from the outset. This study joined others that used the CNN-based segmentation approach and its variants for detection in urban environments (Table 4).

Table 4: Summaries of urban segmentation studies based on deep learning

Authors	Objective	Data	Method	Results	Advantages / Limitations
[22]	Automatic building detection	Annotated UAV images	Mask R-CNN	Good accuracy (~95%), sharp outlines	Precise masks/ High cost, sensitive to shadows

Authors	**Objective**	**Data**	**Method**	**Results**	**Advantages / Limitations**
[53]	Segmentation robust to data variations	heterogeneous multi-source UAVs	Combined Segmentation Network (CSN)	dataset generalization	Robust multi-source / Need for large annotated games
[36]	Compare U-Net to classic ML	UAVid2020	U-Net vs RF, MLP	U-Net ~75%, > RF/MLP (~52%)	Simple, effective / Details lost (resizing)
[59]	Efficient and rapid urban segmentation	UAVid , LoveDA , Vaihingen	UNetFormer (U-Net + Transformer)	mIoU 52–84%, very fast (~322 FPS)	Good compromise between speed and precision / Complex, high memory

This work, while not exhaustive, highlights the main advances and limitations of CNN architectures, particularly in urban segmentation. It also demonstrates the challenges and performance achieved in quite different urban contexts. Besides ANN and CNN models, models such as RNN and its variant LSTM are used in urban contexts for classification and simulation of urban development. A rather innovative urban simulation method based on a recurrent neural network (RNN) is proposed by [68]. This approach enabled the modeling of land cover changes using Landsat satellite imagery as input data. This research complements that of [46], who introduced an RNN approach for land cover classification. The approach relies on the spatial correlations of different land cover classes. Additional training improved accuracy when noise filtering and correction of potential classification errors were performed. [56] introduced a technique based on the multimodal RNN-LSTM variant. The authors used both geospatial and temporal data for urban mobility prediction. This work demonstrates the relevance of LSTM and RNN methods in the analysis, management, and simulation of urban systems, as well as CNN and ANN approaches. However, all the techniques studied so far show a high sensitivity to the quality and resolution of the input satellite data and require significant computing resources. Furthermore, these techniques need to be tested more extensively in different urban contexts, particularly non-homogeneous urban environments, to better ensure the reproducibility of the models and their adaptability to any urban setting. The analysis of all these studies also highlights the need for optimization of input parameters to ensure reliable and accurate results. Therefore, the choice of model will depend heavily on the type of processing, the main objective, the image resolution, the available computing resources, and the type of extraction in the case of segmentation. Knowing the influence of these elements on the choice of AI model, a decision flowchart can guide geospatial researchers and analysts in implementing the algorithm best suited to the urban context, according to their data and objectives (Fig. 1).

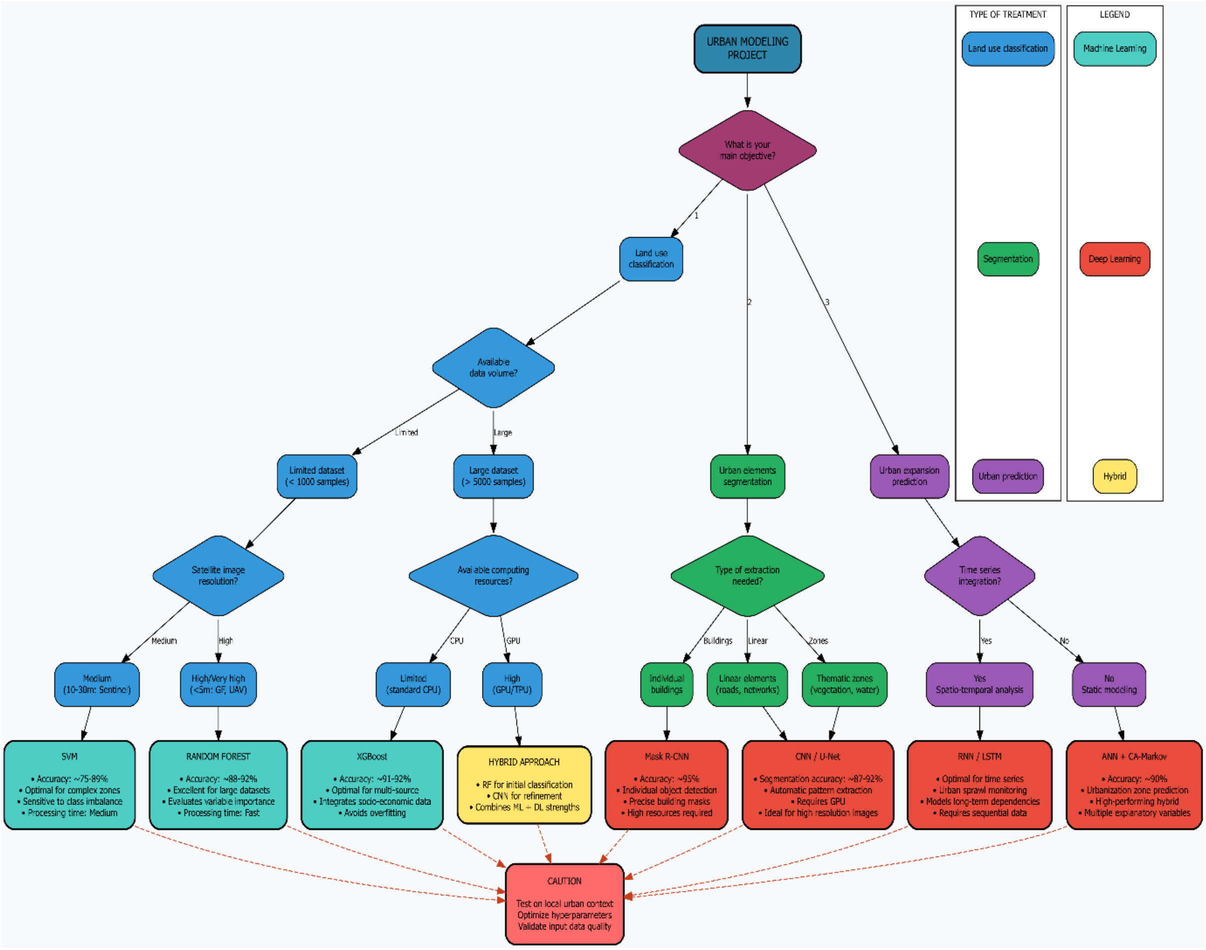

Figure 1: Decision flowchart for the selection of ML/DL algorithms for urban classification, segmentation, and prediction

The flowchart highlights the possible methodologies for accurate urban modeling based on AI techniques. This process relies on several interdependent factors. The use of machine learning algorithms (SVM, Random Forest, XGBoost) stands out as a powerful solution for supervised land-use classification, while deep learning algorithms (CNN, U-Net, Mask R-CNN, RNN/LSTM) are more useful for fine segmentation and complex spatiotemporal models. The flowchart also emphasizes the importance of hybrid methods that combine ANN and CA-Markov to simulate urban expansion. It further underscores the need for rigorous hyperparameter tuning, data quality checks, and local testing to strengthen the models.

V. CONCLUSION

The literature has shown how artificial intelligence has changed the methods of data analysis, visualization, and management in urban environments. Machine learning and deep learning algorithms have become powerful and indispensable tools in the urban context. Machine learning techniques, particularly Random Forest, Support Vector Machine (SVM), and XGBoost, provide high accuracy in land cover classification and modeling. Meanwhile, deep learning techniques (CNN, RNN, ANN, and their variants), in addition to supervised land cover classification, enable the automated extraction of physical elements in urban environments (buildings, roads, etc.) through image segmentation [15, 3]. The two sets of models are therefore complementary. However, despite their computing power and their ability to process large, complex datasets, the literature has shown that these algorithms are sensitive to the quality and resolution of the satellite and/or drone images that are often used as input data in the processing. The computing resource requirements of these algorithms, in addition to the fact that the urban prediction process only takes into account physical factors and does not consider socio-economic variables, are also comparable to empirical prediction methodologies, namely: SLEUTH and CA-Markov. This aspect does not really affect their ability to be combined with non-physical data such as demographic data [13].

The scientific community continues to test and implement these modern techniques in urban space management, but it remains important to apply them more widely in heterogeneous urban areas, particularly in developing countries where urban space does not follow pre-established urban patterns and where there is a real lack of research on the application of AI in the urban context. This approach would allow for verification of the reproducibility of these algorithms in diverse contexts.

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